A Deep Neural Network Approach for Prediction of Aircraft Top of Descent

Hao Jie Ang[1)], Qing Cai[1)], and Sameer Alam[1)†]

[1)] *Air Traffic Management Research Institute, School of Mechanical and Aerospace Engineering, Nanyang Technological University, 639798, Singapore*

[†] *email: sameeralam@ntu.edu.sg*

Abstract— An arrival flight starts to transit from the cruise phase to the descent phase at the top of descent (TOD). Pilots get to know the TOD locations via onboard devices, while controllers can estimate the TOD locations with the help of radar surveillance and simple rules. In order to help controllers to get a better situation awareness of the traffic surrounding an aerodrome, it is of great operational importance to get an accurate prediction of the TOD locations for arrival flights. In this paper, we propose to apply deep learning for TOD location prediction for arrival flights. To do so, a TOD-specific feature engineering is suggested and applied to historical flight trajectories. Then the simple yet effective multilayer perceptron neural network model is adopted for TOD prediction. A case study on the arrival flights to Singapore Changi airport with respect to one-month historical trajectory data is carried out. Experiments demonstrate that the adopted deep learning method is effective for TOD location prediction. When compared against several typical machine learning models for regression, the adopted model yields a mean square error of 0.0039, which is smaller than the error achieved by the comparison models. Meanwhile, the adopted deep learning model yields TOD location prediction errors of 0.29 nautical miles (NM) on average with a standard deviation of 46.88 NM.

Key Words : Air Traffic Management, Top of Descent Prediction, Deep Learning

1. Introduction

An arrival flight starts to descend from the TOD point to meet certain requirements such as estimated time of arrival, arrival speed restrictions, and so on. TOD is the computed transition point from the cruise phase of a flight to the descent phase, or the point at which the planned descent to the final approach altitude is initiated. The TOD is usually calculated by an on-board flight management system (FMS), and is designed to provide the most economical descent to approach altitude or to meet some other objectives (fastest descent, greatest range, etc.)[1)] The FMS calculates the TOD by "flying" the descent backward from touchdown through the approach and up to cruise. For airline FMS, this is a very sophisticated and accurate prediction.[1, 2)]

TOD also can be calculated manually as long as distance, air speed, and current altitude are known. This can be done by finding the difference between current altitude and desired altitude, dividing the result by the desired rate of descent, and then multiplying that figure by the quotient of the ground speed (not airspeed) and 60. The result dictates how far from the destination descent must begin. From the TOD, the vertical navigation (VNAV) determines a four-dimensional predicted path.[3)] As the VNAV commands the throttles to idle, the aircraft begins its descent along the VNAV path. If either the predicted path is incorrect or the downpath winds are different from the predictions, then the aircraft will not perfectly follow the path.[3)] The aircraft varies the pitch in order to maintain the path. Since the throttles are at idle this will modulate the speed. Normally the FMS allows the speed to vary within a small band. After this, either the throttles advance (if the aircraft is below path) or the FMS requests speed brakes with a message such as "ADD DRAG" (if the aircraft is above path).

In order to maintain separations between arrivals, aircraft may be required by ATCOs to level off for a given time period. All these lead to the widely seen step-down descent (SDA) or dive-and-drive approach. Step-down descent approach (SDA) or dive-and-drive has always been the preferred descending method of an aircraft as compared to Continue descent approach (CDA). ICAO defines CDO as "an aircraft operating technique aided by appropriate airspace and procedure design and appropriate ATCO clearances enabling the execution of a flight profile optimized to the operating capability of the aircraft, with low engine thrust settings and, where possible, a low drag configuration, thereby reducing fuel burn and emissions during descent. The optimum vertical profile takes the form of a continuously descending path, with a minimum of level flight segments only as needed to decelerate and configure the aircraft or to establish a landing guidance system (e.g. instrumental landing system (ILS))."

Note that aircraft performing CDA have more benefits as compared to SDA.[4–7] In busy airports, CDOs are often applied in off-peak hours only.[8] In order to improve airport capacity as well as to promote CDO operations, an accurate prediction of the TOD locations could be extremely valuable. The TOD location of an arrival flight affects its fuel consumption. It also can determine whether the flight can do CDO or not. An accurate prediction of TOD locations for arrival flights not only facilitates CDO management, but also helps reduce ATCOs' workload for safety maintenance.[9,10]

From the perspective of pilots, they often use a large variety of descent-planning techniques, even for the same equipment. These techniques vary in terms of the selection of descent angle, bottom-of-descent planning, and TOD transition. Sometimes they take into account winds aloft and weight, but rarely descent speed. With the availability of an intelligent tool, pilots operations could be standardized. Such standardized procedures lead to better trajectory predictability and provide benefits for separation assurance. In the literature, many CDO related researches have been done by scientists. Several analytical models have been developed to predict TOD for both SDA and CDA.[11,12] Some analytical methods also have been developed to design the optimal TOD profile for CDOs.[2,13,14] However, the major drawback of those methods is that they require certain assumptions and therefore may not accurately capture the non-linear relationship between TOD and its dependent factors.

In order to provide an accurate prediction of the TOD location for an arrival flight to assist ATCOs with pre-tactical and tactical traffic management, in this paper we propose to apply deep learning techniques which require no prior-knowledge and model assumptions. To do so, we first analyze historical flight trajectory data and identify the TOD locations from the data. We then develop a feature engineering to extract possible features from the trajectory data and a training dataset is therefore generated. Finally, we apply the well-known multi-layer perceptron neural network to learn a regression model from the training data. The learned regression model is able to predict the TOD location for a given arrival flight. In order to validate the effectiveness of the proposed approach, a case study on arrival flights to Singapore Changi airport is carried out. Experiments demonstrate that the proposed deep learning-based approach is capable of predicting TOD locations for arrival flights. As compared to several representative machine learning models, the proposed approach yields the smallest mean square errors, while the average error of the predicted TOD locations is 0.29 NM.

2. Related Background and Motivation

2.1. Aircraft Top of Descent

TOD is the computed transition point that a flight transits from the cruising phase to the descent phase. Fig. 1 shows an example of the descent trajectory of an arrival flight and it corresponding TOD location.[9]

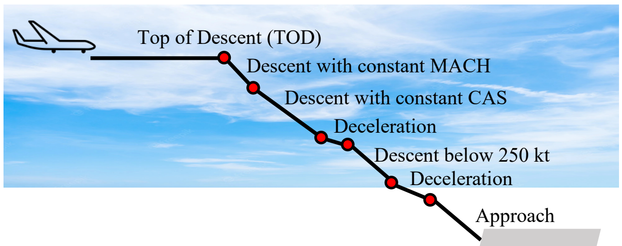

Fig. 1. An example of the TOD location for an arrival flight.

Note that Fig. 1 only presents an example of the vertical profile of an arrival flight. For real traffic scenario, the vertical profile of an arrival flight may differ from what is shown in Fig. 1.

2.2. Estimation of TOD

TOD estimation is both important for pilots and ATCs. In the literature, there are normally three methods for TOD estimation. Those three methods are briefly described in what follows.

2.2.1. On-board FMS

Pilots make use of the onboard FMS to calculate the TOD to provide the most efficient descent profile for the aircraft and also to meet certain objectives such as the longest descent range, fastest descent rate, controlled time of arrival, and so on. The FMS computes the TOD of an aircraft by using information such as flight plan, aircraft model, descent wind, etc. However, the equations used by the FMS are proprietary and therefore are not known to ATCOs.[12]

2.2.2. Rule of Thumb

The Rule of Thumb is normally used to get a rough estimation of the TOD. The glide slope for an arrival is assumed to be 3-degree. Given the cruising altitude and the destination altitude, then the TOD is estimated as the difference between the two altitudes divided by 300. For example, say the altitude difference is 30000 feet. Then the TOD is approximately estimated as 30000/300=100 NM. Note that the TOD calculated using the rule of thumb is the estimated distance from the TOD point to the destination altitude. An online toolkit for approximate TOD distance estimation can be found at https://descent.vercel.app.

2.2.3. Machine Learning Based Approach

In the literature, there are several machine learning approaches for TOD estimation.[11, 12, 15)] Those methods apply representative regression models to capture the non-linear relationship between TOD and its dependent factors. For example, the authors in[15)] proposed a decision-tree model to predict the TOD location based on important flight parameters such as the flight level,approach heading, ground speed and aircraft type. The author in[12)] used a multi-regression model to learn the relationship between TOD and factors including aircraft type, cruise altitude, cruise Mach number and wind parameter. As mentioned earlier, the main drawback for machine learning-based methods is that they require prior-knowledge and model assumptions.

2.3. Research Motivation

Note that only large aircraft are equipped with performance-based FMS for accurate and efficient TOD calculation, while small aircraft are equipped with simpler Vertical Navigation (VNAV) capabilities. The FMS based TOD calculation is either based on a company-programmed default or a pilot-selected value. Regarding the Rule of Thumb method, it only provides a rough estimation of the TOD, which then deteriorates the implementation of CDO. As for traditional machine learning-based methods, since they require prior-knowledge, therefore are not suitable for CDO.

In an event where there is high traffic density at the airport, ATC may face difficulty separating the flights that have close TOD locations. Therefore, ATC may not have enough time to plan the separation in time, leading to a high ATC workload and holdings demanding extra fuel burn.

This paper aims to apply deep learning method to assist ATC with a better prediction of flight TOD location. An accurate prediction of TOD locations for arrival flights can provide ATC more flexibility and manage time to enable more expeditious and environmentally friendly flow management. Eventually, this model could be implemented as one of the tools that can assist ATC and pilots with CDO.

3. Research Problem and Methodology

3.1. Research Problem

The TOD location information is critical both to pilots and ATCs. Difference TOD locations of an arrival flight may lead to different fuel consumption and type of descent approach (SDA, CDA). Although pilots can calculate the accurate TOD using FMS, the calculated TOD may be subject to ATC intervention to meet requirements such as planned separation.

In this paper, we aim to predict the TOD location for an arrival flight using deep learning approach to facilitate ATCs with better arrival management. The deep learning-based approach should be able to effectively predict the TOD location for an arrival flight once provided with the basic information of the focal arrival flight.

3.2. Methodology Overview

In this section, the methodology used to predict the TOD locations for arrivals will be elucidated in detail. The concept diagram on the methodology is illustrated in Fig. 2.

As can be seen from Fig. 2, the proposed approach involves several key process. Each of the processes will be explained in detail in the following subsections.

3.3. Data Pre-processing

One of the most important steps in every deep learning task is the pre-processing of the input data. In order to predict the TOD locations for arrivals, historical aircraft trajectory data is needed. In this work, the flight trajectory data used is obtained from the Quick Access Recorder (QAR) that is located within the aircraft and provides quick and easy access to the raw flight data. During the entire flight journey, the QAR records the flight parameters so as to enable routine monitoring of aircraft systems and flight crew performance. Some common parameters that the QAR recorded are flight datetime, lateral acceleration, vertical acceleration, fuel flow, Mach number, coordinates, angle of attack, airspeed, wind speed, departure and arrival airport. Due to the nature of raw flight data, pre-processing is needed to filter out the target data. Firstly, the trajectories for arrivals are filtered out based on the destination airport. Next, the trajectories with insufficient information including time information and GPS information are removed. At last, interpolation techniques were applied to impute the selected trajectories with missing information. We also notice that some trajectories have abnormal altitude changes. We therefore apply simple mechanisms to smooth the trajectories.

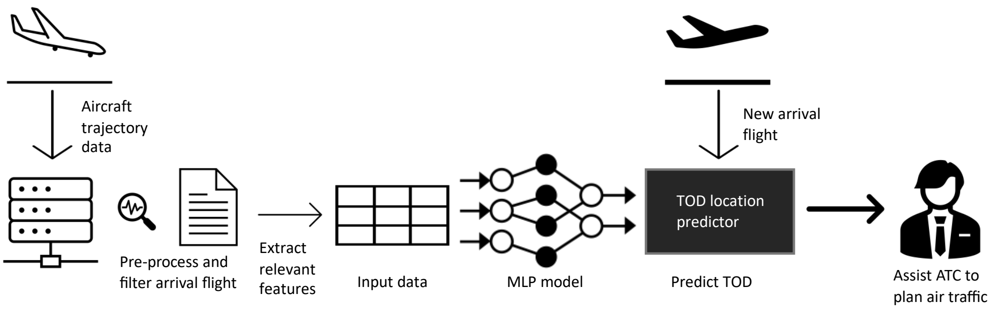

Fig. 2 Concept diagram of the proposed deep learning method for prediction aircraft TOD location.

3.4. TOD Identification

After the arrival flights have been filtered from the aircraft trajectory data, the TOD location for every arrival flight trajectory has to be identified for subsequent deep learning purpose. In order to find the TOD, Algorithm 1 is developed to determine the TOD of every arrival flight.

Algorithm 1 TOD location identification.

Input: Arrival flight trajectory
Output: TOD location

```
1. TOD_Location = [ ];
2. alt = trajectory.altitude; // obtain alt
3. alt = smoothdata(alt, 'movmedian', 20); // smooth the alt
4. alt_max = roundn(max(alt)/1000, 0)*1000;
5. upper = alt_max + 300; // height keeping performance
6. lower = alt_max - 300; // a buffer of 300 feet
7. alt(alt < upper & alt >= lower) = alt_max;
8. TF = islocalmax(alt, 'FlatSelection', 'all'); //locate local maximum alt
9. GPS_ID_localmax = find(TF == 1);
10. GPS_ID_CL = find(alt >= lower);
11. GPS_ID_TOD = intersect(GPS_ID_localmax, GPS_ID_CL);
12. TOD_Location = trajectory(GPS_ID_TOD(end));
```

Algorithm 1 utilises the latitudes of an aircraft's trajectory to locate the TOD position. To do so, a data smoothing technique (step 3) is first applied to a given trajectory. Then the altitudes of the trajectory are further modified by considering the height keeping performance (steps 4-7). Eventually, the local maximum altitudes are identified and the last one (TOD) is therefore determined.

3.5. Feature Engineering

3.5.1. Selected Features

There are a couple of factors that affect the TOD locations. Some of these key parameters are aircraft type, cruise altitude, ground speed, airspeed and wind speed. In order to get a more accurate prediction of the TOD locations, in this work we also consider other factors. All the considered factors (features) are recorded in Table 1.

Table 1 Extracted features for deep learning model.

Features	**Type**	**Representation**
MACH	Numerical	Normalization
Ground Speed	Numerical	Normalization
Altitude	Numerical	Normalization
Approach Speed	Numerical	Normalization
Gross Weight	Numerical	Normalization
Wind Direction	Numerical	Normalization
Wind Speed	Numerical	Normalization
Computed Airspeed	Numerical	Normalization
Heading	Numerical	Normalization
Static Air Temperatute	Numerical	Normalization
Aircraft Subtype	Categorical	One-hot Encoding
Latitude	Numerical	Normalization
Longitude	Numerical	Normalization

As recorded in Table 1, 11 input features are considered for the deep learning purpose and 2 coordinate features are considered as the output/labels for the supervised learning process.

3.5.2. Feature Representation

As can be seen from Table 1, some of the features are of numeral type, while the rest of them are of categorical type. In this work, two feature representation methods are applied to normalize the features.

1) Min-max Normalisation: For numerical features, they have been normalized into the range [0, 1]. This is to ensure that all the numerical features are within the same range so as to mitigate the impact of features with a large magnitude.

2) One-hot Encoding: For categorical features, one-hot encoding is utilized to convert the categorical features into one-hot vectors. This is to ensure that different categories have the same importance before training. Meanwhile, one-hot encoding is also a promising way for feature expansion.

3.6. Deep Learning Architecture

Different from existing methods which mainly utilize model-driven approaches for predicting TOD, we propose to apply data-driven techniques to do TOD prediction. Specifically, we aim to train a deep neural network model using historical trajectory data for TOD location prediction.

In this research, we apply the very simple yet effective deep neural network architecture, i.e., multilayer perceptron (MLP), for TOD location prediction. MLP is a type of feed-forward artificial neural network consisting of three layers minimum, viz., input layer, hidden layer, and output layer.

To train a neural network model, the activation function is one of the most important design considerations. The activation function will determine how the weighted sum of the input is distributed to the neurons connected to the next hidden layer or output layer. In the MLP model, all the hidden layers typically use the same type of activation function and the output layer will use a different function depending on the application of the MLP model.

In this research, the activation function used in the hidden layer is the rectified linear activation (ReLU) function which is the most common function used in deep learning. The activation function for the output layer is the linear activation function. The loss function considered for MLP is the mean squared error (MSE) as the problem being solved is a regression problem. The optimization algorithm used to train the MLP model is the Adaptive Moment Estimation (Adam) algorithm. Adam is a replacement optimization algorithm for stochastic gradient descent for training deep learning models.

4. Experimental Study

In order to validate the effectiveness of the proposed method, in this section we carry out a case study on the arrival flights to Singapore Changi airports with respect to historical real flight data.

4.1. Historical Flight Data

In the case study, one-month historical flight trajectory data for arrival flights to Singapore Changi airport is used. The arrival flights consist of four aircraft types, viz., A330, A350, A380, and B777. The basic properties of the data are recorded in Table 2.

Table 2 Basic properties of the arrival flight data.

Aircraft Type	#Total Flights	#Arrivals
A330	1855	921
A350	886	381
A380	725	336
B777	2746	1330
Subtotal	6212	2968

As can be seen from Table 2, the trajectory data records trajectories for 6212 flights including arrivals and departures. We then filter out the arrival flights based on the destination airport code 'WSSS'. Eventually, the trajectories for 2968 flights are obtained.

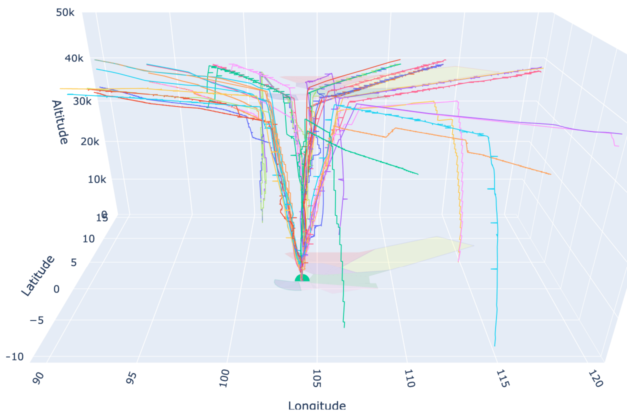

Fig. 3 Demonstration of the arrival flight trajectories.

After the data pre-processing, trajectories for arrivals for December 2019 are obtained. Fig. 3 demonstrates the trajectories for the arrival flights. Different colors represent different flights.

4.2. Real TOD Locations

The TOD locations of the arrival flights are to be used as the labels for the subsequent deep learning purpose. As presented in section 3., Algorithm 1 is developed to identify the TOD locations from the arrival trajectories.

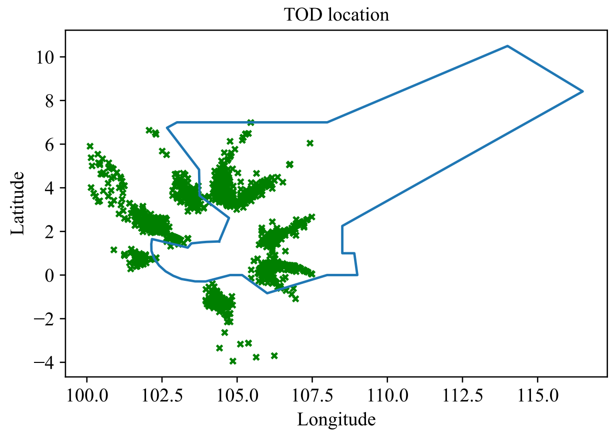

Fig. 4. Demonstration of the TOD locations for the arrival flights obtained from the traffic data.

Fig. 4 demonstrates the TOD locations for the arrival flights obtained using Algorithm 1. We can see from Fig. 4 that most of the TOD locations are near or within Singapore FIR. However, there are still many arrival flights whose TOD locations are outside Singapore FIR. This is normal as we have observed from the data that flights departing from origins such as Thailand start to descend before entering Singapore FIR.

4.3. Experimental Settings

These experiments are carried out using Python programming language and Python packages of Scikit Learn and Tensorflow. All the experiments are done on a MacBook laptop with an 8-Core i7 CPU and 16 GB of Memory.

Table 3. Settings of the machine learning models for prediction purpose.

Model	Settings
MLP	Input Layer: 16 units Hidden Layer 1: 30 units, Relu Hidden Layer 2: 25 units, Relu Hidden Layer 3: 20 units, Relu Output Layer: 2 units, linear
LinR	– –
DecTR	Criteria: Mean Square Error Splitter: Best
SVR	Kernel: Radial Basis function (rbf) Epsilon: 0.05

Regarding the deep learning architecture, we apply the widely used MLP to do the prediction. In the experiments, a 4-layer MLP neural network architecture is utilized. Apart from the MLP model, we also apply several typical machine learning models for prediction purpose. Specifically, we apply the linear regression (LinR) model, the decision tree regression (DecTR) model, and the support vector regression (SVR) model. The settings of those models are shown in Table 3.

Table 4 Different configurations for the MLP model.

Config	Settings
1	Input Layer: 16 units Hidden Layer 1: 30 units, Relu Output Layer 2: 2 units, linear
2	Input Layer: 16 units Hidden Layer 1: 30 units, Relu Hidden Layer 2: 20 units, Relu Output Layer: 2 units, linear
3	Input Layer: 16 units Hidden Layer 1: 30 units, Relu Hidden Layer 2: 25 units, Relu Hidden Layer 3: 20 units, Relu Output Layer: 2 units, linear

For the MLP model, different configuration settings are used to improved the prediction accuracy. The different configuration settings are shown in Table 4.

Based on Table 4, we can see that the difference in the configurations is the number of hidden layers and the number of units in each hidden layer.

4.4. Learning Performance

After applying the MLP model based on the three different network configurations to the input data, the training loss plot is demonstrated in Fig. 5 and the corresponding prediction performance with respect to several metrics is shown in Table 5.

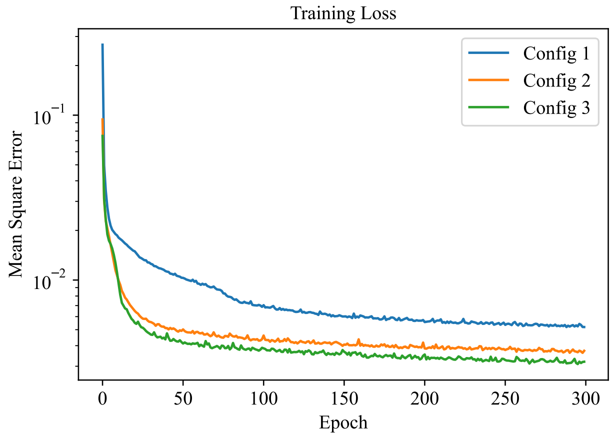

Fig. 5. Training loss of the MLP Model using different network configuration settings.

Table 5. Performance of MLP with different network configurations for 20 independent runs.

Metric	Config 1	Config 2	Config 3
MSE	0.0069	0.0047	0.0037
MAE	0.0544	0.0477	0.0413
MAPE	0.2136	0.1850	0.1594
R^2	0.8327	0.8813	0.9056
err_avg	1.08 NM	4.95 NM	-1.73 NM
err_std	58.92	50.83	46.10

From Fig. 5 and Table 5, we can see that the MLP model using the third configuration has the best performance as it produces the lowest MSE and highest R^2 value. The MLP model with the third network configuration performs the best. In the following experiments, we fix the network structure of the MLP model to be that of configuration 3 as shown in Table 4.

4.5. Predicted TOD Locations

Based on configuration 3, the MLP model is applied to the testing dataset which is 20% of the input dataset. The testing dataset will be first split into their respective aircraft types that consist of A330, A350, A380 and B777. Next, the MLP model is applied to each aircraft type to predict the TOD locations. The predictions of the TOD locations and the actual TOD locations for each aircraft type are shown in Fig. 6.

We can see from Fig. 6 that most of the predicted TOD locations are very close to their targets, while some of them do not coincide quite well with their targets. In order to see how far away the predicted TOD locations are from the targets, we further calculate the geographical distances between them. The distribution of the TOD errors in NM for each of the aircraft types is shown in Fig. 7.

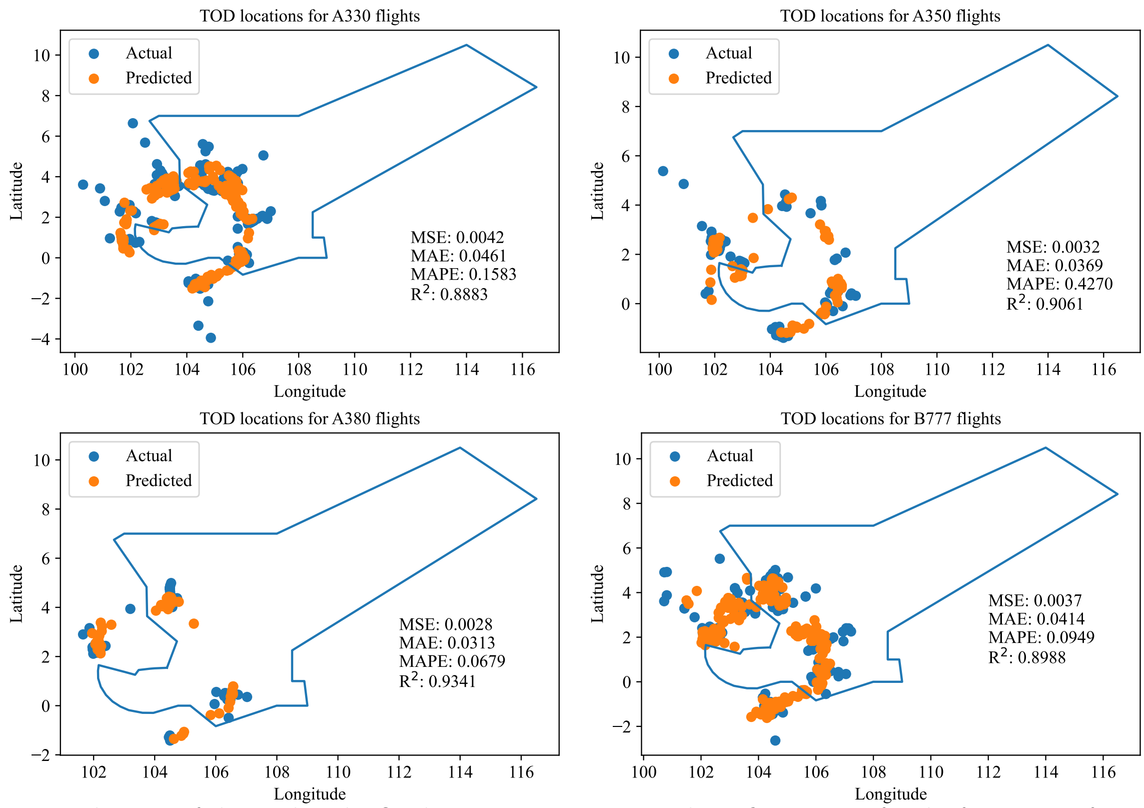

Fig. 6 Visualization of the predicted TOD locations using MLP with configuration 3 for the four types of aircraft.

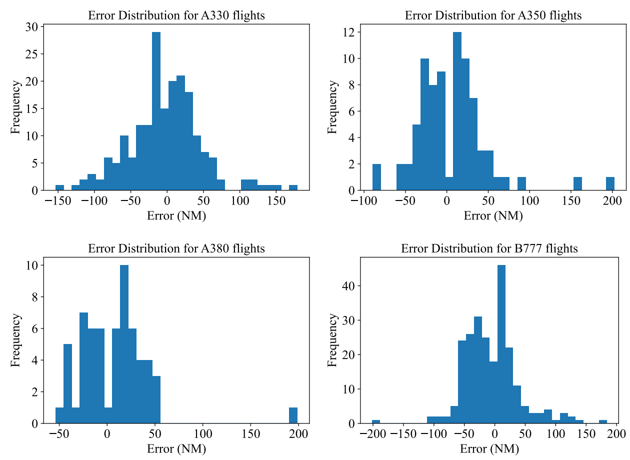

Fig. 7. Distributions of TOD location prediction errors for different aircraft types.

From Fig. 7 we can see that the majority of the TOD errors are approximately within the range of [-50, 50] NM. The performance of the MLP model and the compared machine learning models is shown in Table 6 the metrics obtain from the MLP model configurations 3 to show the with respect to several key performance indicators.

From Table 6 we can see that the MLP model performs better than the other machine learning models. The MSE, MAE and MAPE values obtained by MLP model are lower as compared to those obtained by other

Table 6 Model prediction performance comparison.

Metric	MLP	LinR	DecTR	SVR
MSE	0.0039	0.0188	0.0052	0.0072
MAE	0.0418	0.1026	0.0378	0.0596
MAPE	0.1527	0.3370	0.1665	0.1931
R^2	0.8995	0.5182	0.8652	0.8176
err_avg	0.29 NM	0.38 NM	0.31 NM	-1.68 NM
err_std	46.88 NM	104.27 NM	55.01 NM	62.13 NM

machine learning models. The R^2 metric as shown in Table 6 also indicates that the predicted TOD locations using MLP are quite close to the targets.

4.6. Useful Discussions

Based on the results shown in the above section, we can see that the MLP model is effective for predicting the TOD location. Although the results shown in Table 6 indicate that the MLP model outperforms other machine learning models for TOD location prediction, the results shown in Fig. 6 and Fig. 7 still shown that some of the predicted TOD locations are still far away from their targets. We plan to solve this problem in the next-step research from the following aspects.

1) Weather Data. Although we have considered 11 features that can affect the TOD locations, there are still other factors such as weather that can impact the locations of TOD. ATCOs could issue new instructions to pilots with respect to weather conditions and TOD

locations therefore may be changed. The weather impact will be considered in the next-step research.

2) Standard Instrument Arrival Routes (STARs) Information. Different arrivals can choose different STARs depending on their origin aerodromes. Therefore, different choices of STARs may lead to different TOD. In the next-step research, STARs will be considered.

5. Conclusion

In this research, a deep learning method based on MLP model was proposed for predicting the TOD locations for arrival flights. The MLP model was trained on a one-month historical flight trajectory dataset. The trained regressor was then applied to predict the TOD locations for arrival flights to Singapore Changi airport. Experimental results showed that the MLP model was effective for TOD location prediction. The MLP model yielded an average prediction error of 0.29 NM while the majority of the prediction errors were within the range of [-50, 50] NM. The MLP model was further compared against several typical machine learning models. Experimental results showed that the MLP model outperformed those machine learning models in terms of MSE, MAE, MAPE and R^2. This research will assist ATCOs with CDO operations and aerodrome congestion mitigation.

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